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Decarbonizing power and transportation at the urban scale: An analysis of the Austin, Texas Community Climate Plan

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ABSTRACT

Despite the growing importance of cities in climate change mitigation, there remains a dearth of rigorous analysis to inform municipal climate policies and mitigation strategies. Our study addresses this gap in the literature. We develop an energy system optimization model for urban-scale decarbonization, and use it to analyze the Community Climate Plan adopted by Austin, Texas. Austin is a valuable testbed for analysis because it is a member of the C40 Cities Climate Leadership Group and its goal of net-zero greenhouse gas emissions by 2050 is particularly ambitious. We find that this policy objective can be achieved at a modest 2.7% increase in net present power and transportation costs relative to business-as-usual. The optimal decarbonization pathway proceeds through two distinct stages, first reducing power sector emissions, then electrifying transportation. Solar PV expands in the long run with or without the climate plan based on favorable cost projections, but the policy causes wind to replace natural gas as a complement to solar PV. Results also highlight the substantial value of intelligently scheduled battery storage operations and electric vehicle charging.

1. Introduction

Cities are assuming a prominent role in climate change mitigation efforts. The C40 Cities Climate Leadership Group committed to limiting global warming to 1.5 °C has expanded its membership to 92 cities that encompass 25% of global GDP and 8% of global carbon dioxide equivalent (CO_2e) emissions (C40 Cities, 2018a; Center for Climate & Energy Solutions, 2018). Municipal governments from New York City (The City of New York, 2017) to London (Greater London Authority, 2016) to Tokyo (Tokyo Metropolitan Government, 2007) are implementing detailed climate action plans to reduce greenhouse gas (GHG) emissions. Given the concerns and uncertainties surrounding the future of the Paris Agreement (Rogelj et al., 2016; Tollefson, 2017), the emergence of cities as mitigation agents is an encouraging trend.

Despite the growing importance of cities in climate change mitigation, there remains a dearth of rigorous analysis to inform climate policy and mitigation strategy development at the city level (Rosenzweig, Solecki, Hammer, & Mehrotra, 2010). Our study addresses this gap in the literature. We formulate an energy system optimization model in the Open Source Energy Modeling System (OSeMOSYS) framework (Howells et al., 2011) to identify cost-effective, urban-scale decarbonization pathways. It focuses on power and transportation, and captures key synergies between mitigation strategies in the two sectors. For our case study, we apply the model to evaluate the Community Climate Plan adopted by Austin, Texas in 2015. Austin is a valuable testbed for analysis because it is a member of the C40 network, has a rapidly growing population, and its Community Climate Plan established a particularly ambitious goal of net-zero GHG emissions by 2050.

The remainder of this article is organized as follows. The literature review in Section 2 covers city climate plans, energy system models, and synergies between power and transportation. Section 3 describes our methodology including the model and data sources. We present and discuss results in Section 4. Lastly, Section 5 concludes our article with a summary of its most salient findings, acknowledgment of limitations, and directions for future work.

2. Literature review

2.1. Climate policy approaches

Climate change mitigation can be viewed as a collective action problem in which individual actors make independent decisions whose outcomes jointly affect everyone (Ostrom, 2010). Climate change mitigation is a global public good; the costs are borne locally, but the benefits are distributed globally. The conventional approach to climate

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policy thus holds that, without an appropriate policy framework at the global scale, individual actors have insufficient incentives to curb their own emissions. The desire to establish monocentric (i.e., global) policy solutions is exemplified by international accords such as the Kyoto Protocol (Nordhaus & Boyer, 1999) and recent Paris Agreement (Schleussner et al., 2016). Progress on this scale has been slow, and the road ahead is precarious. Analysts warn that the Paris Agreement is too weak to avert dangerous climate change (Rogelj et al., 2016), and even its future is in doubt after President Trump announced his intention to withdraw the U.S. from the pact (Tollefson, 2017).

Ostrom (2010) argues in favor of an alternative, polycentric approach to climate change mitigation. Polycentric efforts involve mitigation activities undertaken by many actors at diverse scales (e.g., household, municipal, regional, national, global), as all of these actors contribute to and stand to suffer from the effects of climate change. A polycentric approach gives communities freedom to define mitigation strategies that best suit local conditions, encourage broad participation, and generate desired co-benefits (e.g., improve air quality, enhance energy access, increase employment). The cumulative effect of polycentric efforts can be significant at the global scale.

2.2. City climate plans

In line with the polycentric approach, many cities around the world have enacted plans to curb GHG emissions at the urban scale. Notable examples include the London Plan (Chapter 5) to reduce emissions to 60% below 1990 levels by 2025 (Greater London Authority, 2016), New York City's commitment to limit global warming to 1.5 °C in alignment with the Paris Agreement (The City of New York, 2017), and the Austin Community Climate Plan to achieve net-zero GHG emissions by 2050 (City of Austin, 2015).[1] The Austin plan is particularly ambitious, and serves as our case study application for the model we develop.

Creating an effective city climate plan requires a detailed understanding of the urban energy system, including an accurate inventory of GHG emissions. Without a reliable inventory, it is difficult for city planners to identify where efforts should be directed (Grubler et al., 2012). Ramaswami, Chavez, Ewing-Thiel, and Reeve (2011) outline several methods of accounting for urban GHG emissions. A “purely geographic production-based” scheme is likely misleading for cities with large electricity imports and commuting across municipal boundaries. Furthermore, how a city's boundaries are defined may lead to dramatically different GHG emissions inventories.[2] A more appropriate accounting scheme for cities might be a “geographic-plus infrastructure supply chain” method that accounts for emissions which occur upstream in key trans-boundary infrastructures that serve the city (e.g., electric grid, road transportation network). A third alternative is “pure consumption-based” accounting that attributes the full GHG footprints of all goods and services consumed by local households and firms to the city inventory. For reference, total consumption-based emissions of 79 C40 cities are 60% greater than production-based emissions, indicating that cities affect emissions far beyond their physical boundaries (C40 Cities, 2018b). Whether a production-based or consumption-based accounting scheme is preferable when considering a city's response to climate change is not immediately clear. On the one hand, production-based accounting aligns with GHG emissions sources over which the city has the most direct influence. On the other hand, consumption-based accounting incentivizes planners to foster more sustainable consumption patterns and urban lifestyles. Hillman and Ramaswami (2010) present GHG inventories for eight major U.S. cities, including Austin.

2.3. Austin Community Climate Plan

Austin is a rapidly growing city with approximately 948,000 inhabitants in 2016, a sharp increase from 790,000 in 2010 (U.S. Census Bureau, 2016). The City of Austin is at the center of a metropolitan statistical area (MSA) that is home to roughly 2,056,000 people and growing at more than four times the rate of the U.S. population as a whole. The MSA is projected to have a population over 5 million by 2050 (Austin Chamber of Commerce, 2018). Despite its demonstrated commitment to sustainability (described below), Austin has relatively high per-capita GHG emissions compared to other U.S. cities (Glaeser & Kahn, 2010). Contributing factors include: a humid subtropical climate that induces strong air conditioning demand; a sizable (but rapidly declining) coal share of electricity generation; a dispersed settlement pattern dominated by single-family, detached houses; and a transportation sector heavily dependent on private automobile use. For addressing emissions, the Austin municipal government has the unique advantage of controlling its electric utility, Austin Energy. In fact, it is the eighth largest publicly owned electric utility in the U.S. (Austin Energy, 2018).

Austin has a strong tradition of promoting sustainability and combating climate change. In 2007, the Austin City Council passed a resolution to “make Austin the leading city in the nation in the effort to reduce the negative impacts of global warming” (City of Austin, 2007). Since then, the City Council has adopted targets to reduce emissions and transition to renewable energy. In 2010, the City Council approved the Austin Energy Resource, Generation, and Climate Protection Plan to 2020 (Austin Energy, 2010), with a goal of meeting 35% of all energy needs with renewable resources by 2020. This renewable share is to feature at least 200 MW of solar power, of which 50% is local solar and 25% is specifically customer-owned solar. Austin has already achieved some ambitious goals. For example, all municipal buildings now operate exclusively on renewable energy.

In 2014, the City Council passed a resolution officially establishing “a goal of reaching net zero greenhouse gas emissions by 2050” (City of Austin, 2014). One year later, the Office of Sustainability produced the Austin Community Climate Plan (ACCP) (City of Austin, 2015) to formalize and delineate this vision. The ACCP aims to set Austin on a path of economic and environmental sustainability, establish Austin as a global leader in addressing climate change, and provide an example policy framework for other cities to follow. Fig. 1 illustrates the GHG emissions path that the ACCP establishes through 2050, including interim targets to be reached along the way. Indeed, Austin plans to exceed the 80% (relative to 2005 levels) reduction in GHG emissions by 2050 which had been targeted by the Obama administration and incorporated into its Intended Nationally Determined Contribution to the Paris Agreement. The plan document acknowledges that Austin is already experiencing climate change impacts including more frequent wildfires and flooding, persistent drought conditions, violent precipitation, recording-breaking summer temperatures, more days above 110 °F, and more nights above 80 °F. It projects that these phenomena will increase in frequency and magnitude over time. At the city scale, these changes could inflict heavy economic, social, and environmental costs.

To develop the ACCP, the Office of Sustainability began by ordering a full GHG inventory for Travis County. This effort followed the recommendations of the U.S. Community Protocol for Accounting and Reporting of Greenhouse Gas Emissions (ICLEI, 2012) and measured emissions in the following categories: (1) use of electricity, (2) use of fuel in residential and commercial air and water heating, (3) passenger and freight travel, (4) landfills, and (5) industrial processes. Some

[1] See Stone, Vargo, and Habeeb (2012) for a review of climate plans from the 50 most populous municipalities in the U.S.

[2] For example, C40 membership applies only to the jurisdictional boundary of the participating city authority. As an extreme contrast, Melbourne's jurisdiction is only the central business district, with an area of 6.2 km^2, whereas London's jurisdiction encompasses all of Greater London, with an area of 1579 km^2.

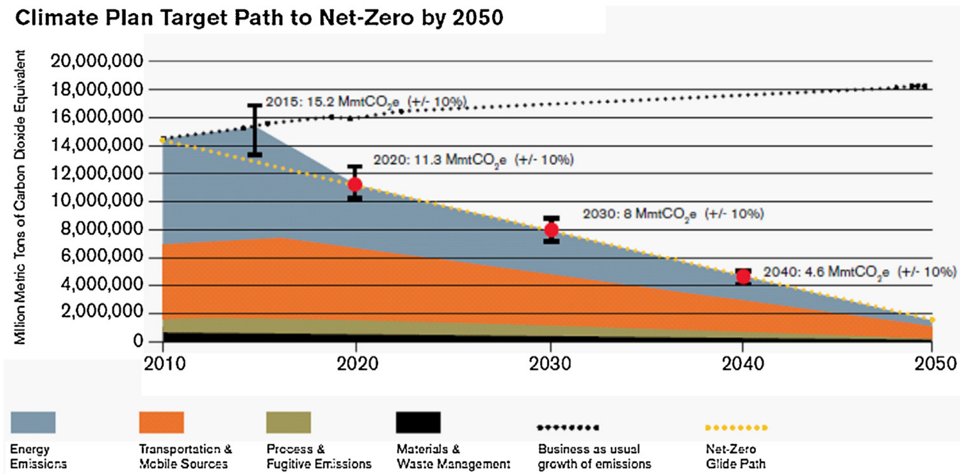

Fig. 1. GHG emissions path through 2050 established in the Austin Community Climate Plan (City of Austin, 2015).

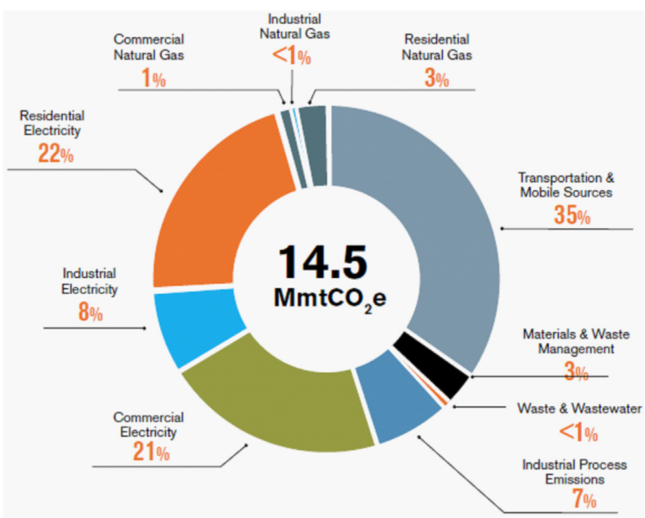

Fig. 2. Austin GHG inventory for 2010 (City of Austin, 2015).

emissions sources, however, were excluded: emissions from the extraction of raw materials, the manufacture and transportation of foods and goods to Austin, upstream emissions from the extraction and processing of fossil fuels, air travel, and natural carbon capture (offsetting emissions). This inventory methodology most closely aligns with the purely geographic production-based accounting scheme. Based on findings from King County, Washington, consumption-based accounting could lead to total emissions that are 160% higher (City of Austin, 2015). The GHG inventory results shown in Fig. 2 reveal a few high-level characteristics of Austin's energy system. First, the use of natural gas as a heating fuel is quite limited in Austin, but electricity generation accounts for over half of all GHG emissions. Second, transportation accounts for 35% of emissions, 94% of which are due to on-road cars and trucks.[3] Third, industrial emissions make up a fairly small share of the total, and are mainly associated with lime production and semiconductor manufacturing. So, the obvious sectors to target for reducing emissions are power and transportation, which combine to produce 86% of Austin's emissions.

The Office of Sustainability convened four technical advisory groups (electricity and natural gas, transportation, waste management, and industrial processes) to define strategies for cost-effectively reducing emissions. The ACCP includes a detailed outline of specific mitigation actions that can be implemented in each sector. Identified actions include improving building energy efficiencies, investing in energy storage technologies and smart grid systems, shifting power generation to renewable energy, and demand-side management. In 2016, the Office of Sustainability released an Implementation Plan for Phase I of the ACCP (City of Austin, 2016), the period leading up to the 2020 interim target. It highlights 58 actions from the ACCP that are expected to contribute to meeting the 2020 target. Austin appears on track to achieve its near-term goal, primarily because Austin Energy has swiftly increased the share of renewables in its electricity generation portfolio.

Finally, the ACCP establishes a rigorous reporting cycle, with frequent revisions, progress reports, and GHG inventories to keep Austin on track to achieve its net-zero goal. In addition to its core environmental purpose, it is hoped that the ACCP will help ensure access to affordable energy and alleviate Austin's congested transportation networks.

2.4. Energy system optimization models

Pfenninger, Hawkes, and Keirstead (2014) distinguish four energy system modeling paradigms: (1) energy system optimization models, (2) energy system simulation models, (3) power systems and electricity market models, and (4) qualitative and mixed-method scenarios. The framework we develop herein belongs to the first of these classes.

Energy system optimization models contain detailed, bottom-up representations of the technological components that constitute an energy system. They are used to explore how energy systems are likely to evolve – or should ideally evolve – over some specified timeframe, depending on techno-economic assumptions and policy settings. An evolution of the energy system is known as a transformation pathway, defined by the collection of all technology investments and operational decisions. Energy system optimization models are typically constructed to identify the least-cost transformation pathway that satisfies all energy demands as well as a host of other constraints. By introducing additional parameters or constraints, energy system optimization models can be used to analyze a range of energy and climate policies. Specific questions that they intend to answer include: (1) Is it possible to achieve an emissions target given available technologies and constraints on their deployment? (2) What is the economic cost of achieving a climate policy goal? (3) What technological transformation pathway allows a policy goal to be accomplished most cost-effectively? Well-known optimization frameworks include the MARKAL/TIMES family (Loulou, 2007; Loulou, Goldstein, & Noble, 2004; Loulou & Labriet, 2007), MESSAGE (Messner & Schrattenholzer, 2000; Messner &

[3] Austin is heavily dependent on private automobile use for transportation and is plagued by traffic congestion. In 2016, the average Austinite spent 47 h in traffic, making Austin the 13th most congested city in the country.

Strubegger, 1995), and OSeMOSYS (Howells et al., 2011).

Despite the growing importance of city mitigation efforts, energy system optimization models are typically applied at the national or global scale. In fact, there are very few examples in the literature describing urban-scale application of these frameworks. Lin, Cao, Cui, Wang, and Bai (2010) employ the LEAP model to study GHG emissions reduction in Xiamen, China. Their model incorporates a variety of mitigation strategies including clean energy substitution (natural gas largely replaces coal and diesel in industry and transportation), renewable energy development, and motor vehicle control. They find that clean energy substitution is the most effective measure. Comodi, Cioccolanti, and Gargiulo (2012) use the TIMES model to analyze the effects of several climate policies in Pesaro, Italy, a small seaside municipality. The authors find that carbon policies promoting the diffusion of solar technologies reduce energy consumption, but are costly for residents. Ma et al. (2015) apply the MARKAL model to Shanghai, China, a city plagued by intense coal use. Under a climate policy, coal is gradually replaced by natural gas, which reduces emissions. They do not, however, consider transportation. Rosenzweig et al. (2010) argue that far more research is needed on urban-scale mitigation in order to guide city governments toward effective policy solutions. The present article addresses this gap in the literature, advancing the application of energy modeling at the city level, and using this approach to evaluate an enacted city climate plan rather than a set of hypothetical policy scenarios.

2.5. Synergies between power and transportation

The power and transportation sectors are the two largest GHG emitters in the U.S., accounting for 29% and 27% of total emissions, respectively (EPA, 2017b). Evidence suggests that these shares are even higher in urban areas, and in Austin these two sectors account for 86% of emissions (see Fig. 2). Any serious effort to decarbonize cities will therefore require monumental changes in how we generate electricity and travel from place to place. At present, transportation and power are largely decoupled, at least in the U.S. Petroleum products dominate the fuel mix of the former, but have been almost completely phased out of the latter. This situation is likely to change in the future as transportation shifts to alternative fuels that are more closely linked to the power sector, especially under climate policies (Anandarajah, McDowall, & Ekins, 2013; Bosetti & Longden, 2013; Edelenbosch et al., 2017; Pietzcker et al., 2014). Amid this trend, powerful synergies will emerge whereby mitigation activities in power and transportation mutually enhance one another. We design our model to leverage these synergies while optimizing decarbonization pathways.

Use of electricity as a transportation fuel causes larger marginal GHG emissions reductions as the power sector decarbonizes upstream. This is one reason why most energy-economy models choose to decarbonize electricity generation before investing significantly to convert transportation fleets to electric vehicles (Löffler et al., 2017; Pietzcker et al., 2014). Electrification of transportation would increase overall demand levels in the power sector, necessitating greater capacity utilization and/or additional capacity investments. Hydrogen fuel cell vehicles can also provide carbon-free transportation if hydrogen is produced via electrolysis using renewable electricity (Anandarajah et al., 2013). So, the hydrogen route to sustainable mobility is also enhanced by decarbonizing the power sector.

In the reverse direction, uptake of alternative fuel vehicles facilitates the integration of intermittent renewables into the power sector and provides valuable services to the electric grid. Electric vehicle charging can be managed as a flexible load to absorb renewable electricity during periods of excess supply. Choi, Kreikebaum, Thomas, and Divan (2013) demonstrate that intelligently scheduling electric vehicle charging reduces the cost of complying with a renewable electricity standard in the power sector. Hydrogen production via electrolysis can similarly be considered a flexible load, occurring when renewable energy is abundant to provide fuel for hydrogen-based vehicles. In a vehicle-to-grid (V2G) system, electric vehicle batteries are capable of supplying power to the grid at times of peak demand or low renewable resource availability. With widespread adoption of electric vehicles, V2G could encourage further deployment of renewable technologies and reduce investments in peaking power plants or stand-alone energy storage technologies (Nunes, Farias, & Brito, 2015).

3. Methodology

3.1. Standard OSeMOSYS

OSeMOSYS is a highly flexible and modular energy system optimization framework that can be applied to problems ranging in scope from an electricity microgrid to a comprehensive global energy system (Howells et al., 2011). It has much in common with other bottom-up, technologically detailed energy models such as MARKAL/TIMES (Loulou, 2007; Loulou et al., 2004; Loulou & Labriet, 2007) and MESSAGE (Messner & Schrattenholzer, 2000; Messner & Strubegger, 1995). However, unlike these other models, the standard OSeMOSYS source code is publicly and freely accessible,[4] and thus addresses a gap in the existing toolbox while enhancing energy modeling research transparency. The standard version of OSeMOSYS can be run via a user-friendly, web-based interface. Nevertheless, research teams have developed customized OSeMOSYS implementations in a variety of programming environments to tailor the framework to specific problems. OSeMOSYS applications appearing in the literature include high renewable penetration in Ireland (Welsch et al., 2014), electric capacity planning under policy uncertainty (Leibowicz, 2018), climate resilience of African infrastructure (Cervigni, Liden, Neumann, & Strzepek, 2015), and competing objectives in the Saudi Arabian power sector (Groissböck & Pickl, 2016).

OSeMOSYS is formulated as a linear program that determines the least-cost technology capacity additions and operational schedules that satisfy exogenous demands, subject to a host of constraints. The model consists of a collection of component blocks, each of which can be described at four different levels of abstraction: (1) a plain English description, (2) an algebraic formulation of the plain English description, (3) an implementation of the algebraic formulation in a particular programming language, and (4) a parameterization corresponding to the specific energy system being modeled. For example, consider the "Energy Balance" component block. In plain English, "Energy Balance" ensures that in each year, timeslice,[5] and region, production of each fuel is sufficient to satisfy final demand for that fuel plus use of that fuel as an intermediate input to other processes. An algebraic formulation of the essential equation within the "Energy Balance" block is given in Eq. (1).[6] In this study, the third level of abstraction is our implementation of this equation in the General Algebraic Modeling System (GAMS) source code we develop for OSeMOSYS. The fourth level of abstraction is achieved by parameterizing this equation using data for our Austin application. A similar breakdown could be provided for the objective function in Eq. (2), which computes the net present cost of the energy system. Other component blocks model storage, operating constraints, and emissions accounting.

[4] Please see www.osemosys.org for the most up-to-date information about OSeMOSYS.

[5] Energy system optimization models typically divide each year into a computationally tractable number of representative timeslices. These timeslices allow a model to capture temporal variability of parameters such as demands and intermittent renewable resource capacity factors. They also allow a model to solve for simplified operational schedules (i.e., dispatch).

[6] In Eqs. (1) and (2), Y is the set of years, L is the set of timeslices, F is the set of fuels, R is the set of regions, and T is the set of technologies. Corresponding lower-case letters refer to elements of these sets.

$$\forall\, y \in Y,\, l \in L,\, f \in F,\, r \in R, \quad \text{Production}_{y,l,f,r} \geq \text{Demand}_{y,l,f,r} + \text{Use}_{y,l,f,r} \tag{1}$$

$$\begin{aligned}\text{minimize} \quad & \textstyle\sum_{y,t,r} [\text{DiscountedOperatingCost}_{y,t,r} \\ & + \text{DiscountedCapitalInvestment}_{y,t,r} \\ & + \text{DiscountedTechnologyEmissionsPenalty}_{y,t,r} \\ & - \text{DiscountedSalvageValue}_{y,t,r}] \\ & + \textstyle\sum_{y,r} \text{DiscountedDemandResponseCost}\end{aligned} \tag{2}$$

An OSeMOSYS database for a particular application defines “fuels” and “technologies,” terms which have expansive interpretations in the context of the model. A “fuel” is any energy commodity, energy carrier, or energy service that is a process input, process output, or demanded by consumers. The set of fuels can thus include coal, gasoline, electricity, hydrogen, vehicle miles traveled (VMT), and so on. A “technology” is any device that converts input fuels into output fuels. Example technologies that can be defined include coal power plants that convert coal into electricity, steam methane reforming that converts natural gas into hydrogen, and internal combustion engine vehicles that convert gasoline into VMT. Technologies do not necessarily need to have an input fuel. In modeling an electric utility, for instance, coal is purchased rather than produced within the model. So, purchasing coal can be represented as a technology that consumes no input, produces coal as an output, and has only variable cost (i.e., the exogenously specified coal price). Renewable resource potentials are represented in much the same manner, except all costs are zero and quantity constraints are imposed to reflect natural limits on available resources. Certain fuels are associated with many different technologies and demands throughout a database. Electricity can be generated using many combinations of feedstock and power plant, is demanded by consumers, and is an intermediate input to technologies such as hydrogen electrolysis, electric vehicles, and battery electricity storage (for which electricity is also the output). Each technology in the database is represented by exogenously specified parameter values for costs (capital, fixed O&M, variable O&M), capacity factors, residual capacities, efficiencies, lifetimes, capacity and operating limits, GHG emission rates, and so on.

3.2. Model implementation and customization

For this study, we modify the standard OSeMOSYS framework to determine optimal energy system transformation pathways for achieving decarbonization goals at the urban scale. We implement our version of OSeMOSYS in the GAMS language and solve it using CPLEX. Our GAMS code is based on an earlier translation of OSeMOSYS into GAMS by Noble (2012), and extends the code developed by Leibowicz (2018). We build a database for Austin and apply OSeMOSYS to evaluate the ACCP. To ensure that our framework covers the vast majority of GHG emissions in Austin, we fully integrate a transportation sector into the model. This integration requires several modifications to the standard, power-centric OSeMOSYS framework.

First, we add constraints to make private transportation non-dispatchable. While an electric utility can centrally decide how to optimally operate its generator fleet during every hour of the day, the private vehicle fleet cannot be optimally coordinated. That is, if there is a mix of different vehicle types in the fleet, there is no reason to believe that they could be dispatched in ascending order of variable cost in order to satisfy the private transportation demand in a given hour. We handle this distinction by requiring that the production of private vehicle miles by each vehicle type in any timeslice be proportional to its share of the overall vehicle fleet. For example, if electric vehicles comprise 10% of the private vehicle fleet, then 10% of the private vehicle miles produced in any timeslice must come from electric vehicles. This constraint would ordinarily make the model nonlinear, as the fleet size and operational variables are both endogenously determined within the model. To preserve linearity, we exogenously calculate the fleet size needed to satisfy the peak private transportation demand assuming an average travel speed and capacity factor for all vehicles.[7] In addition, we constrain the number of miles a vehicle can travel in a given year; the average American drives less than 15,000 miles annually (DOT, 2017).

Second, unlike conventional fossil fuel transportation technologies, electric vehicles introduce the need to model not only their driving activity, but also their charging activity. In addition, V2G capability, whereby electric vehicle batteries can discharge back to the grid, must be modeled in a way that balances charging, discharging, and driving activity. Indeed, vehicles that are out driving can neither charge nor provide V2G power. Because electricity dispatch is determined endogenously, it is also important to coordinate electric vehicle charging as a flexible load. For example, electric vehicles might be charged during hours of high renewable power output or low electricity demand. Allowing the model to optimize charging schedules may constitute an important synergy between power and transportation that could facilitate the integration of renewables into the electricity mix (Choi et al., 2013). Our formulation includes an electric vehicle battery technology, essentially an aggregation of all electric vehicles, similar in spirit to the formulation of Zakeri and Syri (2015). The battery technology charges at a rate consistent with the aggregate power rating, and the electricity stored is used to power electric vehicles while driving or provide V2G power while idle. Timeslice-dependent capacity factors ensure that only idle vehicles can charge. For example, if 10% of electric vehicles are out driving in a given hour, then the aggregate electric vehicle battery technology can charge at up to 90% of its maximum rate (that is, 90% of electric vehicles are plugged in and available to charge). For V2G discharging, we further reduce these capacity factors to reflect EV owners’ limited willingness to make their vehicles available for V2G at various times. We parameterize nighttime and daytime V2G capacity factors to be 75% and 25%, respectively, of those for charging the battery. For example, if 90% of electric vehicles are idle during a nighttime hour, then 75% of these will be made available for V2G for a resulting capacity factor of $0.9 * 0.75 = 67.5\%$. If 90% of electric vehicles are idle during a daytime hour, then only 25% of these will be made available for V2G (presumably because their owners want to keep their batteries charged up in case they need to drive) for a lower capacity factor of $0.9 * 0.25 = 22.5\%$. Enabling electric vehicles for V2G comes at the capital cost of the power inverter installed at home or in the workplace, parameterized at 1.5 times the cost of power inverters for utility-scale lithium-ion batteries (Zakeri ö Syri, 2015). Our formulation thus allows the model to optimally schedule electric vehicle charging and V2G discharging, and ensures that these activities, along with driving, are mutually exclusive for a vehicle in a given hour.

Third, we add capacity growth constraints to prevent individual technologies from scaling up at unreasonably rapid rates as economic and policy parameters evolve. Without these constraints, optimization-based energy models are likely to yield “bang-bang solutions” where the capacity mix changes radically from one period to another due to a slight change in the relative costs of technology options. Capacity growth constraints are commonly imposed in energy system models (Iyer et al., 2015; Wilkerson, Leibowicz, Turner, ö Weyant, 2015), but are absent from the standard version of OSeMOSYS. We include them in our implementation to place some realistic limits on feasible energy

[7] For example, assuming all vehicles operate at an average speed of 30 mph and 3 million miles are demanded everyday from 5 to 6 PM (peak rush hour), then 100,000 vehicles need to be operating in this hour to satisfy demand. However, only 20% of the available vehicle fleet is on the road at any time, so the size of the total vehicle fleet should be approximately 500,000.

system transformation pathways. Specifically, we constrain the new capacity addition in the current period to be less than some fraction of the previous period's total installed capacity, plus a start-up value that enables initial capacity investment in new technologies with no existing capacity.

Fourth, we ensure that the energy system is capable of satisfying demands even under extreme conditions that are not captured by the representative timeslices. Reducing all variability throughout the year to hourly profiles for representative seasonal days necessarily entails aggregation. For example, the representative timeslices should capture the fact that electricity demand is higher in summer than in winter for a system with strong air conditioning load, but the peak demand hour occurring on the hottest summer day would be averaged away in determining the representative summer profile. Alternatively, by averaging hourly wind capacity factors over a season, the representative profile would not account for certain hours when wind generation is zero. This extreme would be problematic for a system heavily reliant on wind turbines. To address these extremes, we add two constraints to ensure that there is adequate capacity to meet demand during the peak load hour of the year, as well as an hour with zero wind generation and high load. These constraints can be satisfied by dispatchable generators, renewable installations operating at their hour-specific capacity factors, demand response, and one quarter of total storage capacity. The model incurs the cost of any additional capacity required to cope with these extreme hours, but they are not explicitly incorporated into the dispatch computation based on representative seasonal days. This is consistent with the notion that demand peaks drive capacity investments while typical conditions drive operating costs.

Fifth, we add demand response capability to the model. The ability to strategically pay customers to reduce load during high-net-load hours will be increasingly important as the power sector shifts further toward renewables. Leveraging demand response allows a utility to save on operating cost by avoiding the use of high-variable-cost peaking plants, and on capital cost by avoiding additional investments that would otherwise be needed to meet peak load plus reserve margin. In our implementation, the optimization routine chooses the amount of demand response to deploy, and these variables get subtracted from the exogenous hourly demand for a fuel in a given timeslice. Demand response has a stepped supply curve, so that limited amounts of demand response are available at three specified cost levels (low, medium, and high).

Sixth, we integrate purchases of carbon offsets into the model. There is some ambiguity in the ACCP in that Austin emissions are not required to decline all the way to zero, but to some near-zero level with the difference made up by purchasing offsets. Our interpretation is that actual Austin emissions must decline by at least 90% by 2050, and that offset purchases can account for the remainder (up to 10%). By adding an OSeMOSYS technology whose operation reduces the annual emissions level at a variable cost equal to the price of carbon offsets, we allow the model to endogenously choose whether to achieve the last 10% of emissions reductions that the ACCP mandates by directly eliminating those emissions or by purchasing offsets. The 10% maximum is imposed as a constraint on the operations of the offset purchasing technology.

3.3. Austin database

We consider the evolution of Austin's power and transportation sectors in annual time steps from 2015 to 2050. The database includes 72 representative timeslices for each year, corresponding to hourly profiles for representative summer, winter, and spring/fall days. The use of 24-hour profiles is important for faithfully representing intra-day variability in demands and renewable capacity factors, and for modeling the operation of storage technologies. From our perspective, this use of timeslices is a major improvement compared to typical approaches that divide days into far fewer timeslices, such as crude

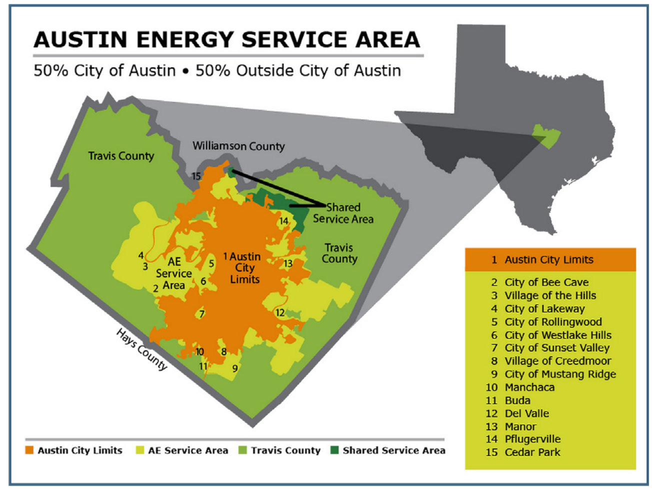

Fig. 3. Austin Energy Service Map of 2015 (Austin Energy, 2018).

daytime and nighttime divisions (Lenox et al., 2013). Our hourly profiles are essential for capturing synergies between the power and transportation sectors, such as flexible electric vehicle charging and V2G storage.

While the ACCP was executed by the Austin City Council, whose jurisdiction is the City of Austin, the GHG emissions inventory ordered is for all of Travis County, of which the City of Austin makes up 81% of the population. Additionally, 97% of Austin Energy's service area is within the boundaries of Travis County (see Fig. 3). Whereas most fossil fuel and solar PV generation occurs in and around Austin, most wind electricity is imported from West and South Texas. Furthermore, Texas transportation data are only available by county, allowing us to capture most commuting activity. Therefore, considering the data collection boundaries and Austin Energy's service area, we take Travis County as the geographical scope of our analysis.

Table 1 lists the technologies included in our Austin database for OSeMOSYS. Transportation technologies are split into two categories: private transportation and public transportation. Furthermore, we use two separate "fuels" to represent private and public transportation demands: vehicle miles travelled (VMT) and passenger miles (PM), respectively. These demands cannot substitute for one another; that is, no portion of private transportation demand can be met by public transportation vehicles, and vice versa. While substitution could occur in the long run, transportation demand in Austin is not expected to shift significantly towards public options due to persistent infrastructural, behavioral, and settlement pattern lock-in effects (Seto et al., 2016).

The database includes three final demand categories: electricity, VMT (private transportation), and PM (public transportation). Our database is unique in that it represents both electricity and transportation demands at hourly resolution for representative seasonal days. Even other models that represent electricity using 24-hour profiles tend to include transportation as a non-time-specific demand. Table 2 provides detailed documentation of data sources for our input parameter value assumptions.

Fig. 4 illustrates the representative demand profiles that are inputs to the model. Fig. 4a shows the average electricity demand profile in each season. Electricity demand is significantly higher in summer due to Austin's humid subtropical climate that induces strong air conditioning load, which peaks in early evening. Heating loads tend to be limited, but because Austin residents predominantly use electric rather than natural gas heating, the winter demand profile has noticeable peaks in the morning and evening. Fig. 4b displays transportation demand profiles for VMT and PM. Note that seasons are not considered, as we have no strong reason to believe transportation demands vary greatly across seasons. Both VMT and PM fall to nearly zero during the

Table 1
Technologies in the OSeMOSYS Austin database.

Power	Coal-fired	*COAL*
Plants	Gas-fired combined cycle	*GAS CC*
	Gas-fired combustion turbine	*GAS CT*
	Nuclear	*NUCLEAR*
	Hydroelectric	*HYDRO*
	Wind turbine	*WIND*
	Solar photovoltaic	*SOLAR*
	Biomass	*BIOMASS*
	Gas-fired combined cycle with carbon capture and storage	*GAS CC CCS*
	Integrated coal gasification combined cycle with carbon capture and storage	*IGCC CCS*
	Hydrogen fuel cell	*H2 FUEL CELL*
Private Vehicles	Gasoline-powered internal combustion	*GASOLINE*
	Diesel-powered internal combustion	*DIESEL*
	Plug-in gasoline-electric hybrid	*PHEV*
	Gasoline-electric hybrid	*HYBRID*
	Hydrogen fuel cell	*H2*
	Electric	*EV*
Public Vehicles	Gasoline-powered internal combustion	*GASOLINE*
	Diesel-powered internal combustion	*DIESEL*
	Compressed natural gas-powered internal combustion	*CNG*
	Biodiesel-powered internal combustion	*BIODIESEL*
	Plug-in gasoline-electric hybrid	*PHEV*
	Gasoline-electric hybrid	*HYBRID*
	Electric	*EV*
Hydrogen Production	Electrolysis	*ELECTROL*
	Natural gas steam reforming	*GASREF*
	Biomass gasification	*BIOGAS*
	Coal gasification	*COALGAS*
Storage	Battery	*BATTERY*
	Electric vehicle battery[a]	*EV BATTERY*

[a] The EV BATTERY technology powers electric vehicles during use and can provide V2G power.

Table 2
Documentation of data sources for input parameter value assumptions.

Parameter	Source
Annual electricity demand	ERCOT (2017b)
Annual electricity demand projections	ERCOT (2015)
Fraction of annual electricity demand in each timeslice	ERCOT (2015)
Annual private transportation demand	TXDOT (2016)
Annual private transportation demand projections	FHWA (2017)
Annual public transportation demand	DOT (2015)
Fraction of transportation demand in each timeslice	DOT (2015)
Average wind capacity factor by timeslice	ERCOT (2017a)
Average solar capacity factor by timeslice	NREL (2016)
Base year power plant capacity mix	Austin Energy (2017)
Base year private transportation fleet mix	TXDMV (2017)
Base year public transportation fleet mix	CapMetro (2016)
Power plant conversion efficiencies	EIA (2017)
Vehicle efficiencies	EIA (2017)
Power plant and fuel cost projections (investment, fixed O&M, variable O&M)	NREL (2017)
Vehicle capital and variable costs, costs for chargers and installation	EIA (2017), Home Advisor (2018)
Power plant CO_2 emission rates	Schlomer et al. (2014)
Vehicle CO_2 emission rates	EPA (2017a)
Battery electricity storage cost assumptions	Zakeri and Syri (2015)
Demand response availability and costs	SPEER (2015)
Hydrogen production costs	Thengane, Hoadley, Bhattacharya, Mitra, and Bandyopadhyay (2014)

night. VMT demand is relatively constant during daylight hours, but exhibits small peaks during the morning and evening rush hours. PM demand is far more concentrated within the rush hours, because a majority of passengers only use public transportation to commute to and from the workplace. Future transportation and electricity demands are taken to be exogenous, and are established based on projections of Austin's population growth (Austin Chamber of Commerce, 2018).

Fig. 5 provides a visual overview of the OSeMOSYS database constructed for Austin. For clarity, it does not represent individual technologies and fuels, as there are simply too many of these in the database to incorporate into an overview diagram. Instead, Fig. 5 depicts the exchanges that take place between different sectors in the model. For example, the hydrogen production and storage sector includes technologies that consume fossil fuels (gray input arrow) and electricity (green input arrow). The hydrogen they produce (blue output arrows) is demanded by hydrogen fuel cells in the electricity generation and storage sector and by hydrogen fuel cell vehicles in the vehicles sector. In addition, demand response may directly lower electricity demand (light blue arrow). Fig. 5 highlights the numerous synergies among electricity, hydrogen, and transportation that system optimization can exploit to identify a universal solution that is superior to the combination of solutions that would be individually optimal for each sector in isolation.

3.4. Policy scenarios

To evaluate the ACCP, we compare a Climate Plan scenario to a Baseline scenario. In particular, we seek to quantify the economic cost of the ACCP, and to assess how the technology mixes of the power and transportation sectors should evolve over time to achieve its decarbonization goal most cost-effectively.

The Baseline scenario is a business-as-usual development of the power and transportation sectors in which investment and operational decisions are optimized in the absence of a carbon policy. The Climate Plan is represented by imposing an exogenous upper limit on emissions in each year, consistent with the linear decline path depicted in Fig. 1. Based on our interpretation, we assume in our Climate Plan scenario that total annual CO_2 emissions must be reduced to zero by 2050, with carbon offsets at most 10% of the difference between 2015 emissions and the exogenous upper limit in each year.

In addition to the Climate Plan scenario with a 10% carbon offset allowance, we also run the model for gradually more stringent variations where the carbon offset allowance is reduced to 8%, 6%, 4%, 2%, and 0%. While we do not report all these results in great detail due to space constraints, it is instructive to see how the policy cost increases as the allowed contribution of carbon offsets is restricted. Furthermore, we conduct some sensitivity analysis on the price of carbon offsets. Eliminating the last few percent of emissions could be very expensive on the margin if offsets are unavailable or their price is high.

3.5. Additional scenarios

In addition to the main Baseline and Climate Plan scenarios, we consider Public Transportation variants featuring significant mode shifting from private to public transportation. Specifically, VMT are gradually converted into PM over the model timeframe so that 50% of VMT from the main scenarios in 2050 is shifted to PM. In converting VMT into PM, we assume that a public bus has an average occupancy of 10 passengers. Indeed, the ACCP advocates shifting transportation demand from private to public modes as an important climate change mitigation lever (City of Austin, 2015). The Public Transportation scenarios thus help us assess the potential benefits of such a transition.

Finally, we also consider Charging Cost variants of our main scenarios in which the cost of electric vehicle battery chargers and their associated installation costs are included in the capital costs of electric vehicles, both private and public. Therefore, the Charging Cost case effectively makes electrified transportation more expensive.

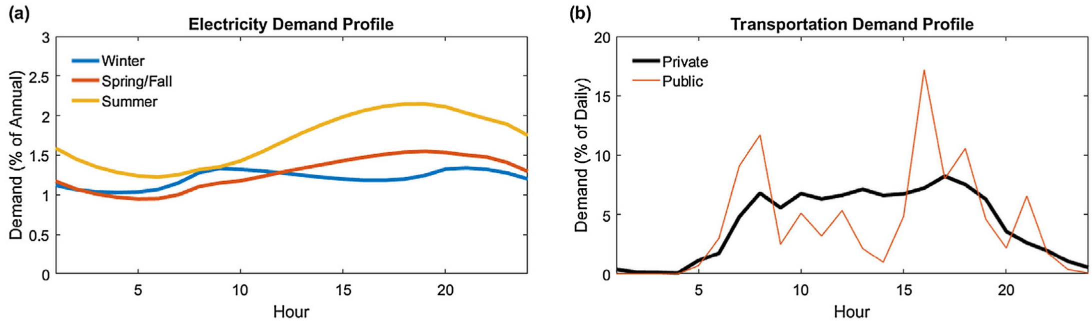

Fig. 4. Demand profiles from the Austin, Texas database that are inputs to the model. The vertical axes measure the percentage of total annual demand occurring in each timeslice. Transportation demand profiles are the same in all seasons, while electricity demand profiles are season-specific. Since spring and fall seasons are combined, the total demand over the two seasons is actually double the orange line values in Fig. 4a, which are averages for the two seasons.

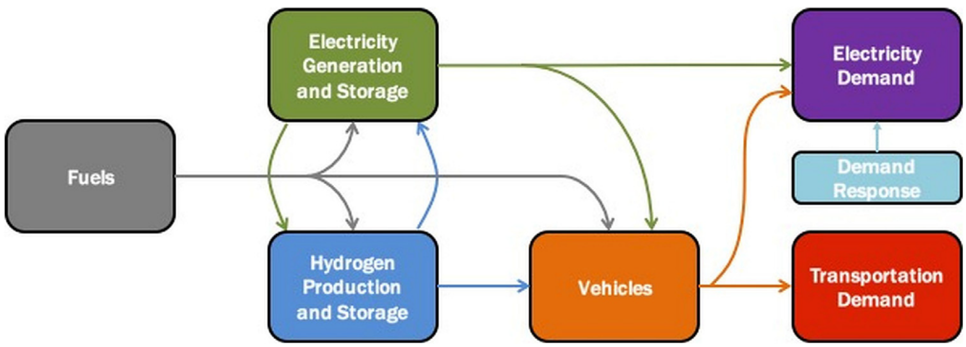

Fig. 5. Visual overview of the OSeMOSYS database constructed for Austin. The diagram highlights synergies among electricity, hydrogen, and transportation.

4. Results and discussion

4.1. Policy cost

OSeMOSYS determines the least-cost transformation pathway for the integrated power and transportation system. The objective value associated with the optimal pathway thus represents the net present cost of satisfying the city's power and transportation demands over the period 2015–2050.[8] By comparing the objective values in the Baseline and Climate Plan scenarios, we can quantify the cost of the policy.

The Baseline scenario results in a net present cost of approximately \$89.0 billion. The corresponding value in the Climate Plan scenario (10% carbon offset allowance) is \$91.4 billion. The Climate Plan restricts the feasible set of solutions that the model has to choose from, so it is unsurprising that the policy increases costs. In relative terms, the ACCP raises net present power and transportation costs by about 2.7%. This economic impact is not trivial, but in our view, 2.7% is a relatively modest cost given the stringency of the ACCP. This result demonstrates that power and transportation can be deeply decarbonized at the urban scale without incurring exorbitant mitigation costs. It also reflects significant cost reductions in clean energy technologies over recent years which have made increasingly ambitious emissions targets economically acceptable.

Ultimately, the policy cost will be borne by residents through some combination of higher electricity rates, the need to purchase vehicles with lower emissions, higher public transportation fares, and additional taxes. Mitigation strategies in the power sector and public transportation can be directly implemented by the city, which controls its electric utility and manages the bus fleet. Getting residents to purchase less emissions-intensive vehicles would require complementary policies such as financial incentives, infrastructure deployment programs, or mandates. Our analysis reveals how the net-zero GHG emissions goal can be achieved most cost-effectively in terms of the system-wide decarbonization pathway, but does not delve into the specific regulations required to induce all components of that pathway.

Fig. 6 illustrates the sensitivity of net present cost to the carbon offset allowance. Reducing the allowance from 10% down toward 0% increases the stringency of the policy by forcing the system to directly eliminate its last remaining emissions. Of course, reducing the offset allowance makes the policy more expensive. Requiring the power and transportation sectors to be totally carbon-free results in a net present cost of \$92.0 billion, roughly \$0.6 billion more than that with the 10% allowance. The relationship between cost and offset allowance is roughly linear except for the difference between the 2% and 0% allowances. The last 2% of emissions are marginally more expensive to eliminate because they necessitate a lot of additional storage capacity and even force public transportation (the most expensive demand to decarbonize) to fully electrify.

We performed some experiments by raising the carbon offset price

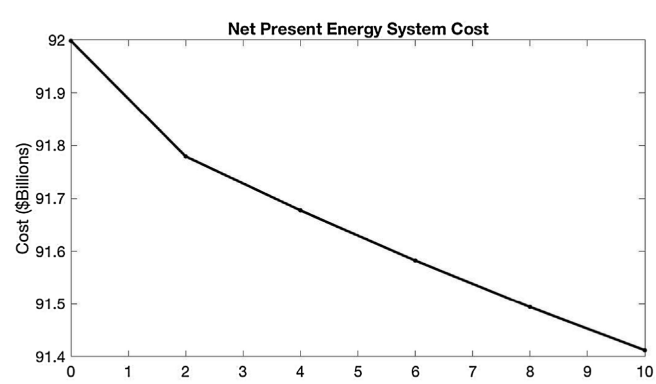

Fig. 6. Sensitivity of the net present cost objective value to the carbon offset allowance.

[8] We assume a relatively standard 5% discount rate.

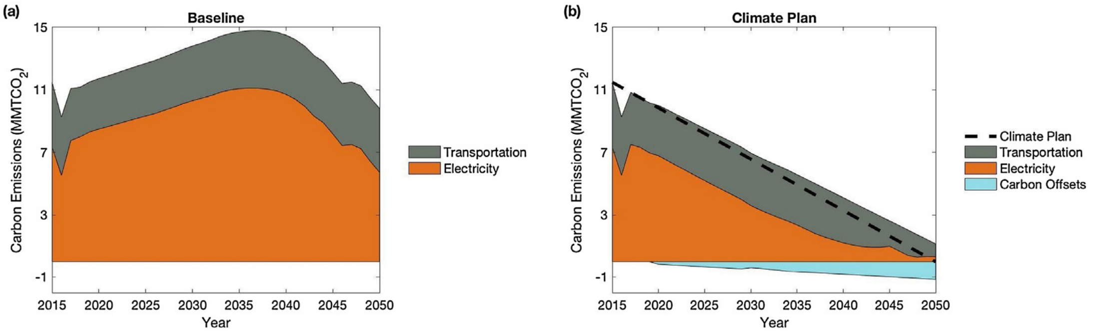

Fig. 7. Annual CO_2 emissions in the Baseline (a) and Climate Plan (b) scenarios, broken down into power and transportation. Carbon offset purchases appear as a negative area because they contribute to satisfying the Climate Plan constraint (dashed black line).

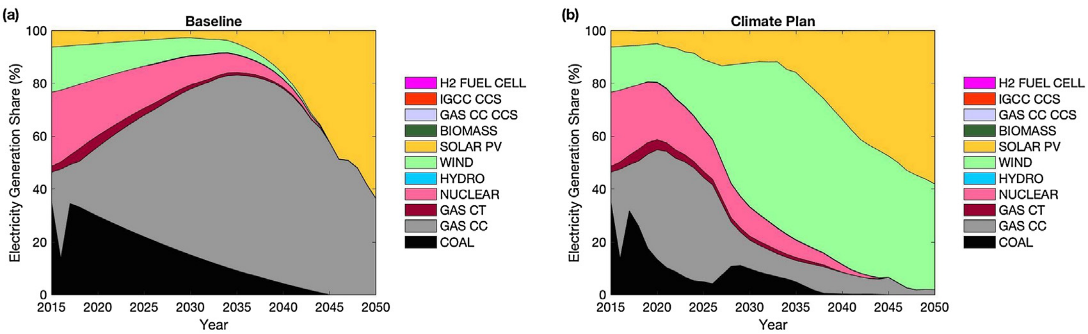

Fig. 8. Evolution of the electricity generation mix in the Baseline (a) and Climate Plan (b) scenarios.

from its reference value of \$20/TCO_2. Interestingly, the offset price has to be many times higher than this for the model to choose to make less than full use of the offset allowance. The constraint on offset purchases remains binding until the price nears \$150/TCO_2, and some offsets are still purchased even when they cost \$200/TCO_2. This observation along with the results in Fig. 6 indicate that actually eliminating the last few percent of emissions is very expensive on the margin.

4.2. CO_2 emissions

Fig. 7 shows annual CO_2 emissions in the Baseline and Climate Plan (10% carbon offset allowance) scenarios, broken down into power and transportation. In the Baseline, total emissions continue to rise until 2038, then decline thereafter. The reductions in later years are confined to the power sector. The Climate Plan total emissions trajectory follows the policy constraint. Fig. 7b exhibits a striking decarbonization pattern with two distinct stages. The power sector is decarbonized first, with transportation emissions only beginning to decline significantly around 2040 when very little CO_2 remains in electricity. This decarbonization sequence, advancing from power to transportation over time, is consistent with prior modeling results at higher spatial scales (Löffler et al., 2017; Pietzcker et al., 2014) and the notion that transportation exhibits strong carbon lock-in (Seto et al., 2016). Austin should focus near-term decarbonization efforts on the power sector (as it is currently doing through Austin Energy), knowing that transportation emissions will need to be addressed in the future once alternative fuel vehicles are cheaper and upstream emissions are lower. This lesson is likely generalizable to most cities.

4.3. Power

Fig. 8 illustrates how the electricity generation mix evolves over time in the Baseline and Climate Plan scenarios. In both cases, there is no new investment in coal power plants. This is significant since coal plants are responsible for 84% of power sector emissions and 53% of all emissions in the 2015 base year.[9]

In the Baseline scenario, GAS CC capacity is continually added through 2036. It is clearly the technology of choice in the near-term, matching the current trend favoring natural gas in the U.S. power sector. The GAS CC generation share begins at approximately 11% in 2015, reaches a peak of 75% in 2039, then declines to its terminal value of 36% in 2050. Optimistic projections for future solar PV costs make it the preferred generation technology in the later years even in the absence of climate policy. By 2050, solar PV accounts for 64% of total generation, with the rest fueled by natural gas. Due to its lower capacity factors, solar PV actually occupies 83% of the terminal capacity mix.

The early years of the Climate Plan scenario see substitution of GAS CC generation for coal electricity, which drops to 4% of the total by 2027 and is completely phased out by 2045 despite a brief utilization resurgence prior to 2030 to accommodate rapid growth of intermittent wind and solar. Wind and solar PV expand aggressively, so much so that they begin displacing GAS CC generation in 2026. This sequence confirms the role of natural gas as a transition fuel in the power sector, aiding decarbonization in the near-term by substituting for coal, but ultimately giving way to renewables once the emissions target intensifies and renewables become more cost-competitive. After the initial years, renewables increasingly dominate the generation mix, and the 2050 mix consists of 40% wind and 58% solar PV (with GAS CC reduced to 2% of generation).

The rapid growth of solar PV begins sooner in the Climate Plan scenario than in the Baseline, but its overall outlook is bullish in either case due to favorable cost projections. Interestingly, the policy context has the biggest impact on the competition between GAS CC and wind for the rest of the future generation mix. The renewable portion of 2050

[9] Coal-fired electricity generation experiences a sharp dip in 2016 due to the natural gas price forecast, which returns to a forecast price of \$2.95/MMBtu in 2016 after an observed price of \$3.22/MMBtu in the 2015 base year. This explains the noticeable kink in Figs. 7 and 8 at 2016.

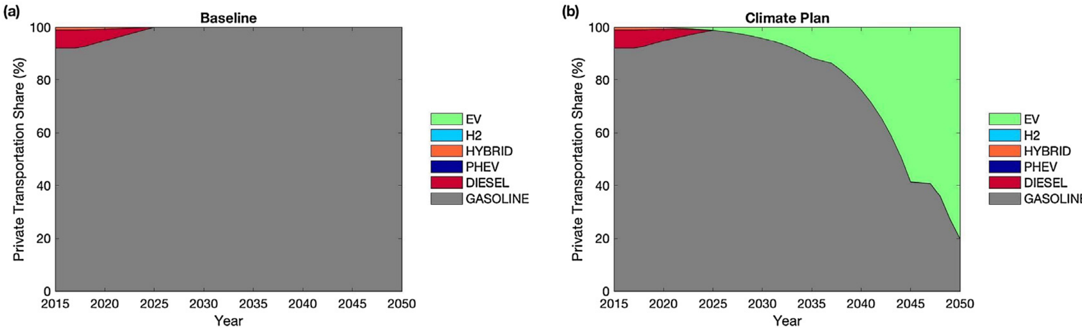

Fig. 9. Evolution of the private vehicle mix in the Baseline (a) and Climate Plan (b) scenarios.

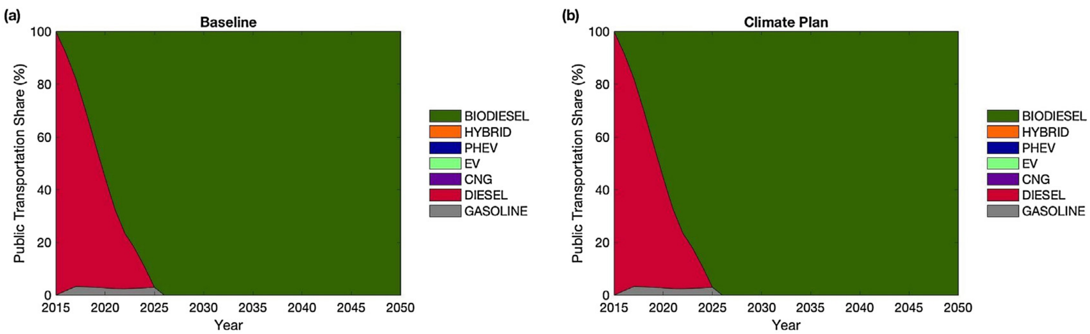

Fig. 10. Evolution of the public vehicle mix in the Baseline (a) and Climate Plan (b) scenarios.

generation in the Baseline is entirely solar PV with no wind. In contrast, the 2050 Climate Plan mix incorporates substantial wind generation. The reasoning is that when renewable penetration is very high, the temporal complementarity between wind and solar PV is very valuable for ensuring that loads can be satisfied. Wind capacity factors in Texas are highest at night when solar PV is unavailable. The picture that emerges is that, in this setting, whether wind and solar PV are substitutes or complements depends on the total share of renewable generation.

It should be noted that total installed capacity in 2050 is greater in the Climate Plan scenario (25.6 GW) than in the Baseline (20.0 GW). This is a consequence of the comprehensive transition to intermittent renewable electricity technologies in the former, which have lower capacity factors than GAS CC. Indeed, by 2050, solar PV and wind capacities are 18.22 GW and 6.82 GW, respectively.

4.4. Transportation

Fig. 9a reveals that private transportation in the Baseline scenario continues to be dominated by gasoline vehicles through 2050. Unlike the power sector, which eventually begins to decarbonize driven by purely economic considerations even in the absence of climate policy, the transportation sector appears unlikely to undergo major change without a policy stimulus. The Climate Plan results in Fig. 9b show that electric vehicles are the most cost-effective technology for decarbonizing private transportation. Their adoption is initially slow and electric vehicles still only account for 4% of the market in 2030. Once the focus of decarbonization shifts from power to transportation, however, electric vehicles diffuse rapidly. They reach 24% market share in 2040 and a much larger 80% in 2050.

The public transportation mix evolves almost identically in the Baseline and Climate Plan scenarios, as shown in Fig. 10. In both cases the fleet shifts strongly to biodiesel buses, which are evidently the most cost-competitive option given our cost and performance assumptions. Public transportation does not respond to the policy because the extreme capital cost differential between carbon-free bus technologies and biodiesel is too large to surmount. The public transportation demand is small but expensive to decarbonize, so carbon offset purchases are allocated first to public transportation, second to the remaining 20% of private transportation that is still fueled by gasoline, and lastly to the 2% of electricity generation that is still fueled by natural gas.

4.5. Demand response, energy storage, and electric vehicle charging

Figs. 11 and 12 show the optimal seasonal electricity dispatch results for 2020 and 2050, respectively. The subfigures compare the Baseline (left column) and Climate Plan (right column) scenarios. In addition to power plant dispatch, they depict demand response, battery electricity storage charging and discharging, and electric vehicle charging. V2G deployment is not selected as part of the optimal transformation pathway in either scenario. Demand response and storage discharging appear as areas above the x-axis, since they effectively contribute to meeting the exogenous electrical loads (represented by the dashed black lines). Storage charging and electric vehicle charging appear as areas below the x-axis, since they add to the exogenous electrical loads. Figs. 11 and 12 therefore reveal how the ability to intelligently schedule and coordinate demand response, energy storage, and electric vehicle operations facilitates cost-effective decarbonization.

Demand response does not feature prominently in the dispatch results for either year, though a small amount of demand response is called upon to meet the summer peak electricity demand in 2020 in the Baseline scenario. Nevertheless, the availability of demand response plays a major role in satisfying the two extreme hour constraints and thus ensuring that the system can cope with a particularly high load or a lack of renewable generation. This is not visible in the dispatch results for the representative seasonal days. The main benefit of demand response is therefore to reduce investment in additional peaking capacity rather than to save money on operating costs.

Energy storage plays a crucial role in the long-term evolution of Austin's energy system. The Baseline transformation pathway includes 28 GWh of battery storage capacity by 2050. The Climate Plan (10%

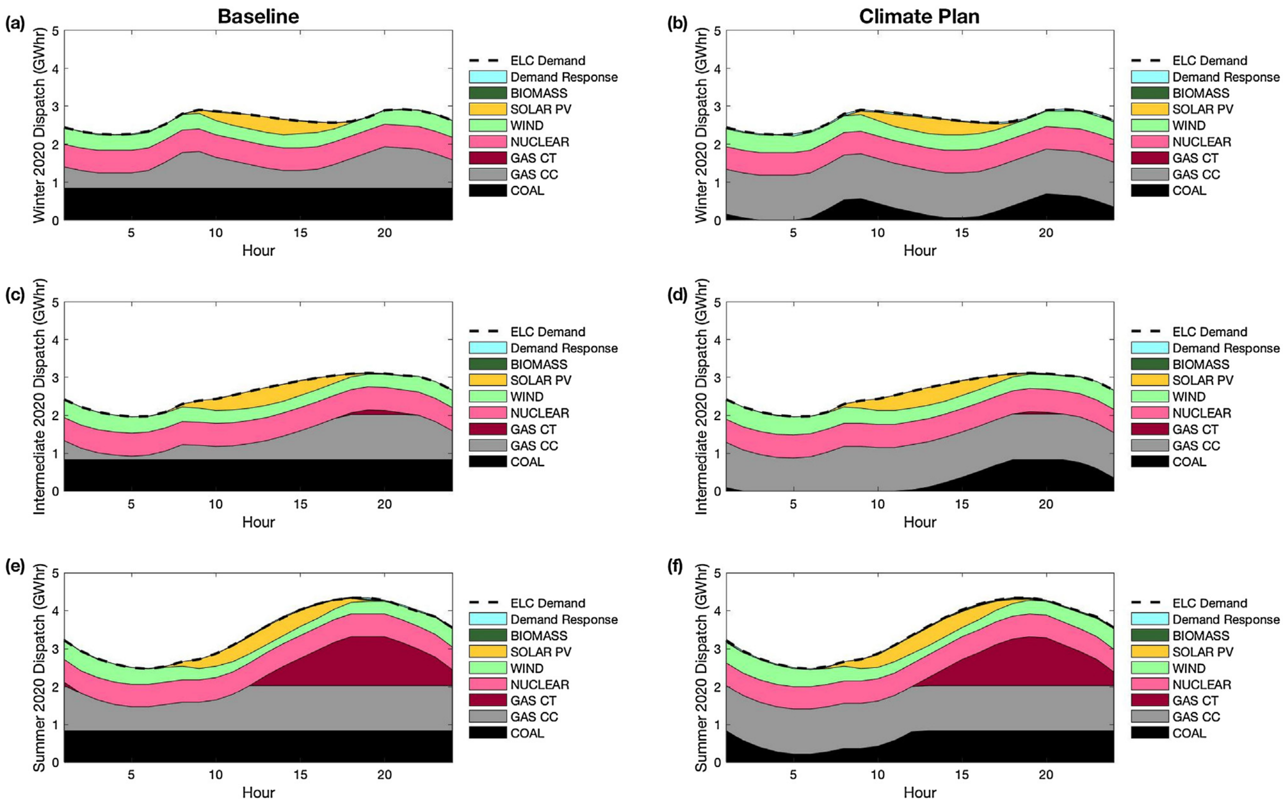

Fig. 11. Seasonal power sector dispatch results for 2020 in the Baseline (left column) and Climate Plan (right column) scenarios. Dashed black lines represent exogenous electrical loads, which do not include demand response (teal area).

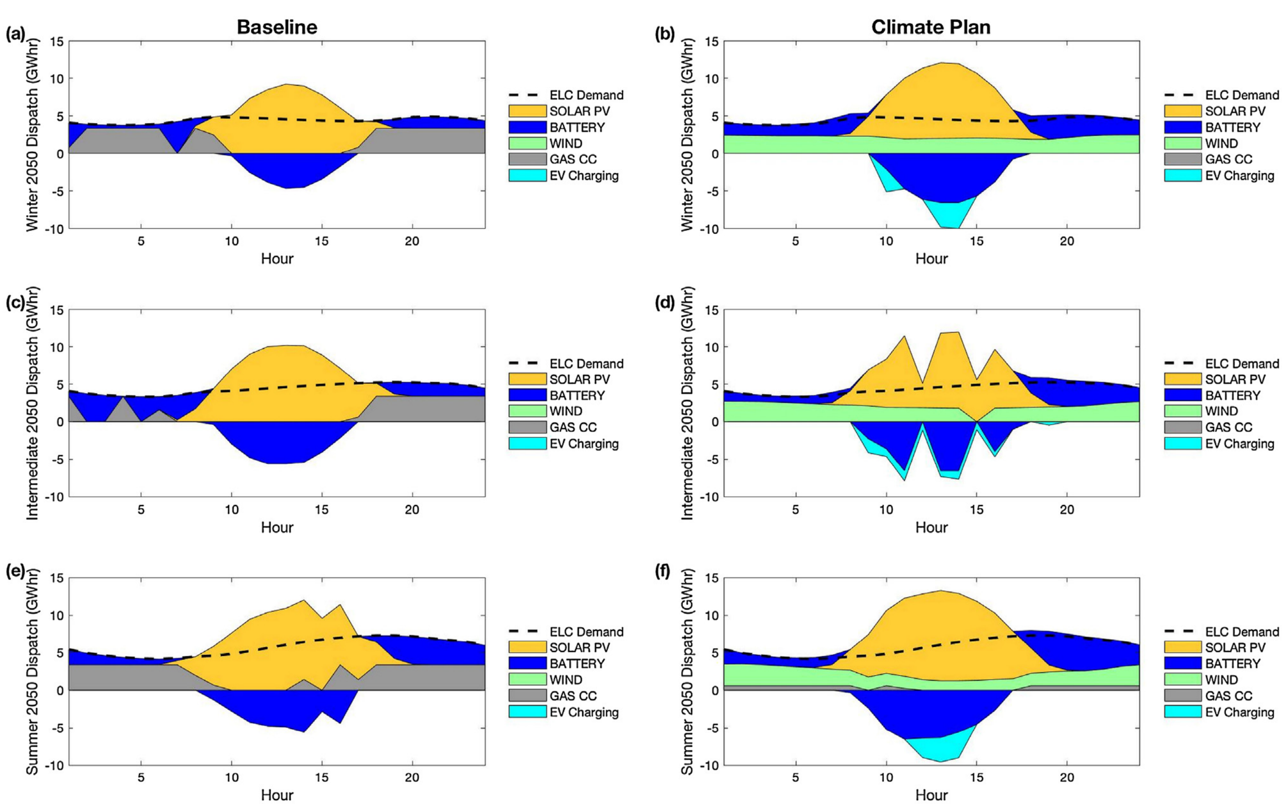

Fig. 12. Seasonal power sector dispatch results for 2050 in the Baseline (left column) and Climate Plan (right column) scenarios. Dashed black lines represent exogenous electrical loads, which do not include battery storage charging (blue area below x-axis), battery storage discharging (blue area above x-axis), or electric vehicle charging (teal area below x-axis).

carbon offset allowance) induces further deployment of battery storage, reaching 36 GWh of capacity by 2050. At the end of the timeframe, solar PV makes up a substantial share of generation in both the Baseline and Climate Plan scenarios. In this context, optimal battery operation essentially follows the availability of solar PV. All the 2050 dispatch profiles in Fig. 12 feature battery charging during the day when solar PV is abundant, and discharging to satisfy the exogenous load at night when solar PV is unavailable.

The electric vehicle charging results in the right column of Fig. 12 demonstrate another synergy between power and transportation under the ACCP. Similar to how batteries charge in a context of high solar PV penetration, optimal electric vehicle charging takes place over the daytime hours when solar PV is abundant. In reaching this outcome, our model implicitly assumes that there are no temporal restrictions on electric vehicle charging, and that charging infrastructure is widely available. We thus interpret our findings to imply that, as the power sector incorporates more solar generation, it will become increasingly important to provide electric vehicle charging infrastructure at workplaces so that coordinated charging can be aligned with solar power output.

Finally, although the jagged pattern of solar PV generation in Fig. 12d may appear strange, it simply reflects the abundance of solar PV capacity relative to the demand for electricity in the intermediate (spring/fall) season. There is more than enough solar PV capacity to meet load, charge battery storage, and charge electric vehicles during the daytime, and none of these activities entails variable cost. So, the model can choose from a variety of dispatch schedules during the daytime hours that all result in the same objective value; the pattern observed in Fig. 12d is one of these.

4.6. Public transportation and charging cost scenarios

In the Public Transportation scenarios, biodiesel buses remain the technology of choice for public transportation. However, with the modal shift toward public transportation, gasoline vehicles remain the dominant technology for private transportation, albeit steadily decreasing to 54% of the private vehicle fleet in 2050 (the rest of which is electric). Since VMT ultimately decline by 50% in the Public Transportation case, it is less critical to deeply decarbonize private transportation. Also, since the higher occupancy of buses means that ten VMT convert into one PM, there are far fewer total vehicles and total vehicle miles in the Public Transportation scenarios. This leads to substantial cost savings in terms of both the absolute net present energy system costs as well as the additional cost of the Climate Plan relative to the Baseline. In the Public Transportation setting, the net present cost is roughly $75.5 billion in the Baseline scenario and $77.3 billion in the Climate Plan scenario. The comparable objective values in the main scenarios were $89.0 billion and $91.4 billion. The policy cost of the Climate Plan beyond that of the Baseline thus decreases from $2.4 billion (2.7% in relative terms) to $1.8 billion (2.4% in relative terms) due to the transition toward public transportation. As previously stated, these benefits stem from the reductions in total vehicles and total vehicle miles enabled by the higher occupancy of buses, rather than changes in the public transportation technology mix. Of course, this Public Transportation setting is entirely hypothetical, and it would likely require major investments in public transit coupled with more compact or transit-oriented land use. It does demonstrate, however, the significant benefits that could result from such a modal shift.

In the Charging Cost scenarios, we include the costs of charging stations and associated installations that consumers typically incur when they purchase electric vehicles. We see no change in the public vehicle fleet, because electric buses were not even chosen in the main scenarios. However, in the Climate Plan scenario, the Charging Cost induces a resurgence of hybrid vehicles in the private vehicle mix beginning around 2030. As Fig. 13b shows, hybrid vehicles later reach a maximum share of 15% in 2045. In the final years of the timeframe, the CO_2 constraint becomes stringent enough that additional hybrid investments are no longer tenable, and electric vehicles increasingly dominate despite added costs for chargers and their installation. Net present energy system cost under the Climate Plan is roughly $0.4 billion higher in the Charging Cost setting than with the main set of assumptions.

5. Conclusion

We developed an energy system optimization model in the OSeMOSYS framework to determine cost-effective decarbonization pathways at the urban scale. For our case study, we used the model to evaluate the Austin Community Climate Plan (ACCP), which establishes a goal of net-zero GHG emissions by 2050. As a member of the C40 Cities Climate Leadership Group with a rapidly growing population and a particularly ambitious climate plan, Austin serves as a valuable testbed for analysis. Our findings thus contribute much-needed insights on how cities can develop sound climate policies and implement effective mitigation strategies. Furthermore, the OSeMOSYS platform we extend is an open source tool, and our hope is that more municipal agencies will employ energy system models to assess potential policy prescriptions.

We find that the ACCP increases net present power and transportation costs by 2.7% relative to business-as-usual. This economic impact is not trivial, but it does demonstrate that even the particularly ambitious net-zero emissions by 2050 goal can be achieved at modest cost. The optimal decarbonization pathway consists of two sequential stages: the power sector is decarbonized first, then the focus shifts to transportation. The ACCP hastens the elimination of coal from the power sector, initially through substitution by natural gas, but increasingly via the expansion of renewables. Solar PV actually comprises a majority of the 2050 generation mix even in the absence of climate policy, based on optimistic cost projections alone. The primary long-run impact of the ACCP on electricity is the replacement of natural gas with wind, which is an effective complement to solar PV under high renewable penetration due to their contrasting temporal profiles (wind at night, solar PV during the day). Once electricity decarbonizes, private transportation transitions to electric vehicles, which are less costly in these later years. Capital cost differentials between carbon-free and conventional options are more extreme in public transportation, which is therefore insensitive to the policy context, even under a scenario of significant modal shift from private to public transportation. Intelligent and coordinated scheduling of battery electricity storage and electric vehicle charging play important roles in the low-carbon transition. Battery storage charges during the daytime when solar PV is abundant and discharges at night when solar PV is unavailable. Optimal electric vehicle charging also occurs during the daytime to align with solar PV availability, which implies that making charging infrastructure available at workplaces would provide substantial system-wide value. Our model does not select V2G or hydrogen technologies in its optimal decarbonization pathways.

Of course, these findings must be interpreted in light of the limitations of the model and database. Our framework has a supply-side focus that does not explicitly incorporate demand-side decarbonization levers (except for demand response) such as end-use appliance efficiency, building efficiency, or urban land-use regulation. Seasonal 24-hour profiles represent intermittent renewable resources and fluctuating demands at higher resolution than most examples in the literature, but they still cannot capture the full range of variability that exists in reality. Due to a lack of available data, our database does not include smaller sources of Austin emissions such as industrial processes, direct natural gas consumption for heating, or landfills. Exogenous parameter assumptions become more uncertain as the analysis timeframe approaches its 2050 horizon. The optimization algorithm assumes perfect foresight, which masks these uncertainties and is known to influence model results (Wilkerson et al., 2015).

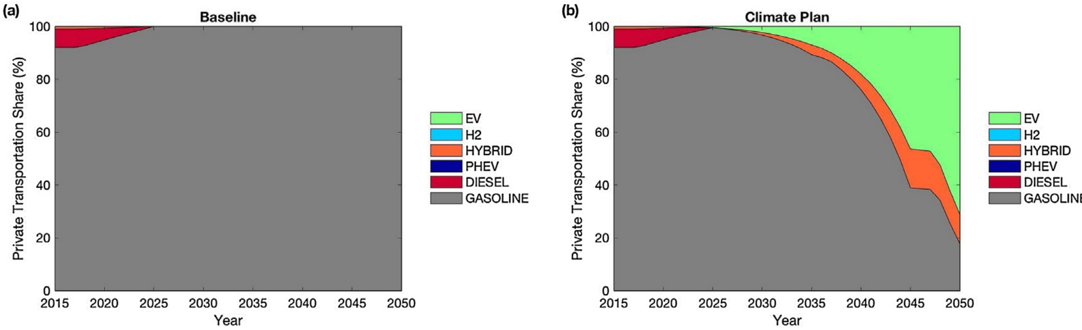

Fig. 13. Evolution of the private vehicle mix in the Baseline (a) and Climate Plan (b) scenarios, with battery charger costs included.

We are continually developing our modeling tools to address these limitations. Efforts currently in progress aim to explicitly incorporate: (1) end-use technology options for satisfying disaggregated energy service demands in the buildings sector, (2) infrastructure networks to transport and distribute energy resources across multiple zones, (3) alternative scenarios for the spatial evolution of the urban built environment, and (4) shared and/or autonomous vehicles. These additional features will allow us to analyze a broader portfolio of mitigation strategies, though obtaining accurate data at the urban scale is always a formidable challenge.

Despite its limitations, this study has contributed much-needed research on city climate plans and urban-scale mitigation pathways. We hope that our insights will provide helpful policy guidance for municipal governments as cities take on a more prominent role in climate change mitigation.

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